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Health Belief Model-based Deep Learning Classifiers for Classifying COVID-19 Social Media Content to Examine Public Behaviors towards Physical Distancing

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Abstract

Background: Public health authorities (PHAs) have been recommending interventions such as physical distancing and face masks, to curtail the transmission of coronavirus disease (COVID-19) within the community. Public perceptions towards such interventions are to be identified so that PHAs can effectively address valid concerns. The Health Belief Model (HBM) has been used to characterize user-generated content from social media during previous outbreaks, to understand health behaviors of people.

Objective: This study is aimed at developing and evaluating deep learning-based text classification models for classifying social media content posted during the COVID-19 outbreak, using the key four constructs of HBM. We specifically focus on content related to the physical distancing interventions put forth by PHAs. We intend to test the model with a real-world case study.

Methods: The dataset for this study was prepared by analyzing Facebook comments which were posted by the public in response to the COVID-19 posts of three PHAs: Ministry of Health of Singapore (MOH), Centers for Disease Control and Prevention (CDC) and Public Health England (PHE). The comments made in the context of physical distancing were manually classified with a Yes/No flag for each of the four HBM constructs: perceived severity, perceived susceptibility, perceived barriers, and perceived benefits. Using a curated dataset of 16,752 comments, a gated recurrent unit (GRU) based recurrent neural network (RNN) model was trained for text classification. Accuracy and binary cross-entropy loss were used for evaluating the model while specificity, sensitivity and balanced accuracy were the metrics used for evaluating the classification results in the MOH case study.

Results: The HBM text classification models achieved mean accuracy rates of 0.92, 0.95, 0.91 and 0.94 for the constructs perceived susceptibility, perceived severity, perceived benefits, and perceived barriers, respectively. In the case study with MOH FB comments, specificity was above 96% for all HBM constructs. Sensitivity was 94.3% and 90.9% for perceived severity and perceived benefits while for perceived susceptibility and perceived barriers, it was 79.6% and 81.5%. The classification models were able to accurately predict the trends in the prevalence of the constructs for the examined days in the case study.

Conclusions: The deep learning-based text classifiers developed in this study help in getting an understanding of the public perceptions towards physical distancing, using the four key constructs of HBM. Health officials can make use of the classification model to characterize health behaviors of public through the lens of social media. In future studies, we intend to extend the model for studying public perceptions on other important interventions of PHAs.

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Keywords: health belief model; physical distancing; COVID-19; text classification; deep learning; recurrent neural network; social media

Introduction

Background

The Health Belief Model (HBM) is a theoretical model constructed based on psychological and social theory [1]. It has been widely used as a conceptual framework in behavioral research to understand the health behavior of individuals. The HBM attempts to explain and predict behavioral outcomes based on two main aspects: the desire to avoid health threat (i.e. infection or illness) and the perception of the effectiveness of behavior adopted to counteract threat. The perception of threat is composed of the perceived susceptibility and perceived severity of an individual to a specific illness or threat. The effectiveness of a specific health behavior is dependent on the interaction between the perceived benefit of the behavior and the perceived barriers to taking actions to mitigate the threat or illness [2]. In addition, cues to actions are prompts or events that trigger the health behavior of interest. Cues to action can be divided into internal (e.g. physical symptoms) or external (e.g. mass media, reminders, advice) triggers. Lastly, health motivation (or self-efficacy) explains how predisposed an individual is to respond to cues to action based on the value of their health. The HBM has been adopted as an explanatory model in communication process [3]. Constructs of the HBM have been used to study health beliefs of public in the social media platform Twitter [4] and analyze postings in Instagram to outbreak communication campaigns [5].

In the context of the ongoing COVID-19 outbreak, the constructs of HBM will be influenced by the interaction of communication made through news and media reports, government policy actions and feedback from public response throughout the course of the outbreak. These messages will in turn alter one's behavior if it targets perceived barriers, benefits, self-efficacy, and threat. One such example is the physical distancing measures put forth by the public health authorities (PHAs) across the globe. Physical distancing measures constitute a combination of measures that aim to increase the physical distance between individuals and reduce the frequency of close contact, which results in lower community transmission of the virus. We note the distinction between physical distancing with self-isolation measures and quarantine orders. Isolation and quarantine measures are for individuals who display COVID-19 related respiratory symptoms and/or have had close contact with confirmed or suspected cases [6]. With the physical distancing measure, the public behavior can be either supportive (desired) or critical (undesired).

The perceptions of the public towards physical distancing can be ascertained by mining the relevant content from social media platforms. PHAs have been using Facebook and Twitter to post regular updates about COVID-19 through their official pages or accounts [7]. Public respond to these updates through comments or tweets. Their opinions could be neutral, supportive, or critical. It is practically difficult for PHA officials to manually analyze the content from social media on a periodic basis. Automated analysis of textual content can be facilitated through machine learning methods such as text classification or categorization. Such methods can be used to dynamically classify bulk social media content for real-time analysis so that PHA officials can gauge public response to their health messages. In a related study, deep learning-based text classification model was used to classify tweets about human papillomavirus vaccine with HBM constructs [4]. Through the study, it was possible to identify the time periods during which the different HBM constructs were prevalent.

This Study

In the current study, we aimed to develop deep learning-based text classification models for classifying social media content posted in response to the COVID-19 updates of PHAs, using the constructs of HBM. The model was tailored specifically for content related to physical distancing intervention. We used the gated recurrent unit (GRU) variant of recurrent neural network (RNN) [8] for building the text classification models. The models were trained and validated with a dataset of 16,752 comments primarily extracted from the Facebook pages maintained by the PHAs of Singapore, the United States (US) and England. As a demonstrative case study for testing, we used the model to classify all Facebook comments received in response to the COVID-19 Facebook posts of Ministry of Health, Singapore (MOH) during the first quarter of 2020. In addition, we created an online demo webpage for bulk classification of social media data (Facebook comments, Tweets) related to physical distancing using the models developed in this study.

Methods

Dataset Preparation

Data for this study were extracted from three Facebook pages using the Facepager tool [9] for the time period starting from 01 Jan 2020 to 31 Mar 2020. The three Facebook pages are officially managed by MOH Singapore [10], the Centers for Disease Control and Prevention (CDC) in the US [11] and Public Health England (PHE) in England [12]. Extracted data include posts by PHAs and comments. From the extracted posts, COVID-19 posts were identified by searching the posts for existence of at least one of the keywords “wuhan virus”, “coronavirus”, “ncov”, “ncov-2019”, “covid” and “covid-19”. The comments received for the filtered COVID-19 posts were subsequently classified using four key HBM constructs: perceived susceptibility, severity, benefits, and barriers. We focused on physical distancing intervention as the preventive behavior of interest. In Table 1, definitions, and sample comments for the HBM constructs are provided in the context of this study.

Table 1. Definition of the Health Belief Model constructs examined and the sample comments in relation to COVID-19

Construct	Definition
Perceived susceptibility	Comments indicating an assessment of the increased likelihood of getting COVID-19 infection, highlighting increasing local prevalence and high importation of cases
Perceived severity	Comments indicating an assessment of increase in the perceived seriousness and the consequences of getting infected by COVID-19 (e.g. hospitalization, pneumonia, death, highlighting mortality risk)
Perceived benefits	Comments supporting, in favor of physical distancing measures (e.g. school closure, working from home, cancellation of events, mass gathering) to reduce transmission of COVID-19
Perceived barriers	Comments mentioning the difficulties, challenges and negative effects of physical distancing (e.g. loss of freedom, violation of individual rights, inconvenience, loss of income, etc.) as well as perceived

	ineffectiveness of physical distancing

The classification of comments for perceived susceptibility and perceived severity was performed using a rule-based filtering method where we used a set of candidate keywords that accurately represented these two constructs. Comments that met the filtering criteria, were flagged accordingly. However, this approach did not work well for perceived barriers and perceived benefits as we could not find an accurate set of keywords that represented these constructs. Hence, the comments were manually classified with the help of two coders. All comments were manually validated using the above-mentioned approaches. Interrater agreement between the two coders was strong. Cohen's kappa scores were 0.91, 0.86, 0.89, and 0.91 for the four HBM constructs perceived susceptibility, perceived severity, perceived benefits, and perceived barriers, respectively. After eliminating blank comments and comments with images, we arrived at a total of 99,197 comments. However, only 8,376 comments (8.44%) represented at least one of the four HBM constructs.

The next step was to prepare a balanced dataset from the analyzed comments for training and validating the text classification models. All 8,376 comments which represented at least one of the four HBM constructs were first added to the dataset. Next, another 8,376 comments which did not represent any of the four HBM constructs were added. As a result, the final dataset comprised of 16,752 comments with 50% of the comments representing preventive behavior (any of HBM constructs). The comments from this dataset were randomly split into training (n=13,401) and validation (n=3,351) sets using the traditional 80/20 split method. Sample comments representing the HBM constructs are provided in the Appendix section.

Text Classification Model

We used for the first time a GRU-based RNN model [8] for classifying content using the HBM constructs. The GRU model is considered as an advancement over the basic RNN model [13] since it addresses the vanishing gradient problem. The gradients carry information used in the updates to RNN parameter and when the gradients become progressively smaller, the parameter updates become insignificant. As a result, no real learning is performed. Hence, learning of long data sequences is hampered due to vanishing gradients. On the other hand, GRU makes use of update gate and reset gate to solve this issue [8]. RNN was previously used in HBM-based models for studying tweets [4]. A bidirectional structure was set for the GRU model since it helps in recording information from both backward and forward states in the neural network [14]. An embedding layer was used as the first layer of the model. Embedding layer is useful in mapping words to a vector of continuous numbers. For this purpose, we used pre-trained GloVe (Global Vectors for Word Representation) word vectors [15], which are pre-trained vectors that map each word to a vector of a specific size. The classification models were implemented in TensorFlow 2.0 [16], comprising of five layers, along with a dropout layer added to avoid overfitting [17]. Accuracy and binary cross entropy loss were the metrics used to evaluate the performance of the models. Other parameters set for the models were as follows. Sequence length, embedding size, vocabulary size and number of units were set to 512, 300, 50,000 and 128, respectively. Adam optimizer [18] was used as the optimization algorithm in the models. In Figure 1, the common architecture of the classification models is illustrated. For each of the four HBM constructs, the model was separately trained and validated. As a result, we obtained four binary classification models with a common design.

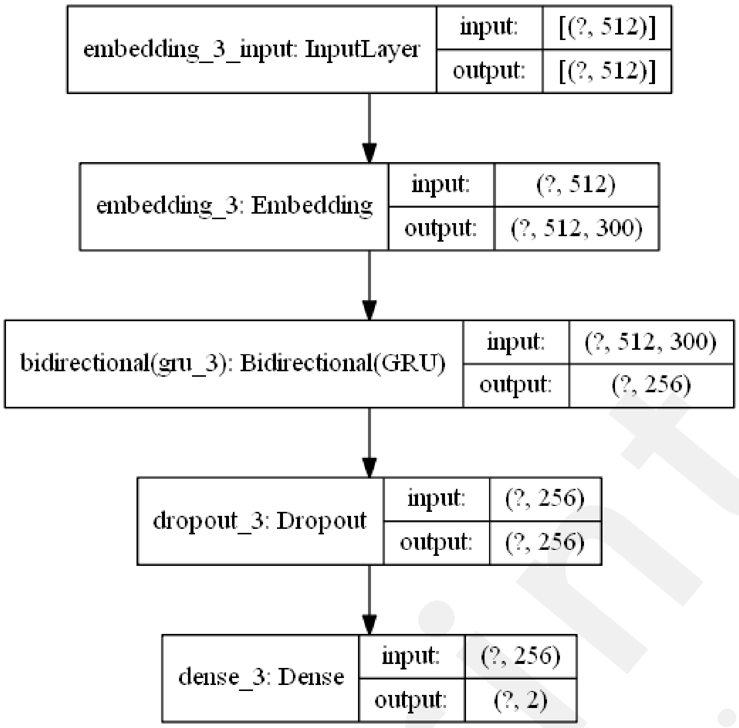

Figure 1. HBM Text Classifier Neural Network Architecture

Results

Classification Performance

In Table 2, the training and validation performance of the models are depicted in the form of mean accuracy and mean loss calculated from six epochs, along with the standard deviation values. All four models had accuracy above 0.91 for both training and validation sets. Perceived severity had the best accuracy (μ=0.95) followed by perceived barrier (μ=0.94), perceived susceptibility (μ=0.93) and perceived benefit (μ=0.91) in training. The validation accuracy values were similar with perceived susceptibility (μ=0.92) being the exception. Through the epochs, the losses gradually reduced for the constructs in both training and validation cycles. Figure A1 in the Appendix section illustrates the loss values by epoch for training and validation.

Table 2. HBM Classification Models' Performance Statistics

HBM Construct	Mean (SD) Training Accuracy	Mean (SD) Training Loss	Mean (SD) Validation Accuracy	Mean (SD) Validation Loss
Perceived Susceptibility	0.93 (0.04)	0.17 (0.09)	0.92 (0.03)	0.23 (0.15)
Perceived Severity	0.95 (0.02)	0.14 (0.07)	0.95 (0.02)	0.11 (0.03)
Perceived Benefit	0.91 (0.03)	0.20 (0.07)	0.91 (0.01)	0.22 (0.01)
Perceived Barrier	0.94 (0.01)	0.15 (0.04)	0.94 (0)	0.15 (0.01)

MOH Case Study

The HBM classification models were used to classify all the comments received for COVID-19 posts of MOH in the first quarter of 2020. We chose the MOH as case study because it was the most active among the three PHAs in posting on Facebook. 9,053 comments were classified as part of this exercise. In Table 3, the specificity, sensitivity, and the balanced accuracy percentages are listed for the four HBM constructs. Specificities were above 96% for all the four constructs with perceived susceptibility and perceived barrier scoring the highest values of 99.7% and 99.0% respectively. However, these two constructs had the lowest sensitivities (79.6% and 81.5%) among the four constructs, clearly indicating that the corresponding models overpredicted false negative cases. Because of skewed specificities, models for classifying perceived susceptibility and perceived barrier achieved balanced accuracy of 89.6% and 90.3% respectively. On the other hand, both sensitivity and specificity were above 90.0% for perceived severity and perceived benefit. Hence, the balanced accuracy for these two constructs was impressive with values of 96.5% and 93.7%.

Table 3. Performance of the HBM Classification Models with MOH Facebook Comments

HBM Construct	Specificity (SP) %	Sensitivity (SE) %	Balanced Accuracy (BA) %
Perceived Susceptibility	99.7%	79.6%	89.6%
Perceived Severity	98.8%	94.3%	96.5%
Perceived Benefit	96.5%	90.9%	93.7%
Perceived Barrier	99.0%	81.5%	90.3%

Note: SP=TP/(TP+FN), SE=TN/(TN+FP), BA=(SP+SE)/2
TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Negatives

In Figure 2, the number of classified comments is plotted as line graphs for comparing the ground truth (manually classified comments) with the deep learning classification results for the HBM constructs. The total number of comments is plotted as an area graph to facilitate interpretation of the prevalence of HBM constructs. The data has been aggregated at week level to facilitate interpretation. Until the end of fourth week (25 Jan), the number of comments representing the four HBM constructs is vividly low. This is primarily because the total comments are also low. There are two peaks periods in the prevalence of HBM constructs, one in week 6 (02 Feb – 08 Feb) and the other in week 13 (22 Mar – 28 Mar). Except for perceived susceptibility, the classification models seem to overpredict when compared to the ground truth. The gap between the actual results and predicted results is visibly evident for perceived benefits in both peak periods. The comments on perceived severity and perceived barriers are overall meagre with only 12.4% and 6.3% prevalence, while perceived benefits and perceived susceptibility accounted for 20.5% and 17.5% of the total comments, respectively.

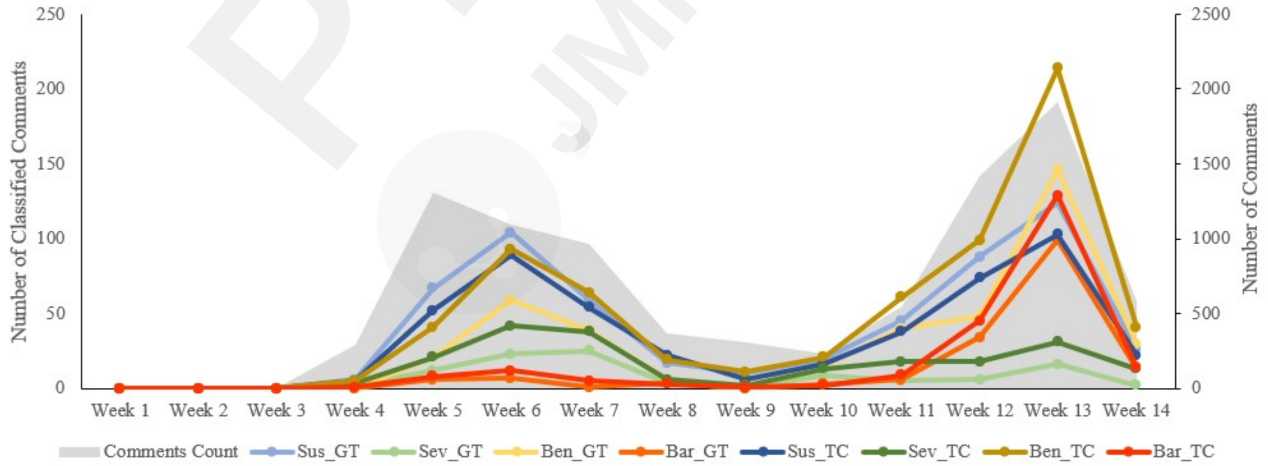

Figure 2. Classification of MOH Comments with HBM Constructs. *Sus* refers to perceived susceptibility, *Sev* refers to perceived severity, *Ben* refers to perceived benefit and *Bar* refers to perceived barrier. Suffixes GT and TC refer to ground truth and text classification, respectively. The primary x-axis is for the classified comments count for the HBM constructs while secondary x-axis is for the total comments count.

Discussions

The similarity in training and validation mean accuracy rates indicate that overfitting and underfitting aspects were minimal, thereby vindicating our strategy of creating a dataset with equal percentage of preventive behavior comments and non-preventive behavior comments. Variable length of comments could be an issue as we noticed that models performed well with longer comments as the context is more discernable. In the case study with MOH Facebook comments, the developed classification models achieved better specificities, sensitivities and accuracies than the previous study [4] where a deep learning model was used to classify tweets with HBM constructs. However, the slightly lower sensitivities of perceived susceptibility and perceived barriers resulted in more false negative cases during classification. The high specificities for all the four models were a result of the skewed nature of the data since only 8.4% of comments in the base set represented at least one of the HBM constructs. Sensitivity is more important than specificity in this study since positive cases need to be more accurately predicted.

The comparison of ground truth with the classification results at the week level indicates that the classification models predict the upward and downtrend trends in a precise manner. There are two peak periods noticed in the prevalence of HBM constructs. The first peak period corresponded to the week when Singapore shifted to Disease Outbreak Response System Condition (DORSCON) orange, the second-highest level of alert for disease outbreaks in Singapore, on 07 Feb 2020 [19]. However, the prevalence of perceived barrier comments did not resemble the other three HBM constructs in this first peak period. The second peak in the prevalence of HBM constructs, did not correspond to any real-world event and we speculate that MOH Facebook page followers started commenting at a higher frequency from this week. Since our data collection ends with 31 Mar 2020, week 14's numbers are partial. In this second peak, the prevalence of perceived barrier increases considerably to indicate that public started talking about barriers to physical distancing at a discernable level from this period. At the same time, the prevalence of perceived severity remained consistently low and did not increase during the second peak.

In the first 13 weeks of 2020, it can be deduced that people talked more about susceptibility and benefits of physical distancing than severity and barriers. At an overall level, the prediction results closely followed the ground truth with no outlying trends, thereby indicating that the classification models can be used to predict trends with HBM constructs in the upcoming months in the context of physical distancing intervention. We have created an online demo webpage to showcase bulk classification of social media content using the developed models [20]. We converted the text classification models to TensforFlow.js (TFJS) [21] format for this purpose. To enable programmatic usage and retraining with new data, the original model files in HDF5 format and converted model files in TFJS files of the four classification models have been made available [22].

There are certain limitations in this study. The comments analyzed in this study should be considered as a snapshot of the overall public response, as users can delete comments In Facebook retrospectively. The opinions of Facebook users regarding physical distancing could be different in Facebook pages other than the PHA page of their respective country. Those opinions are not covered in this study. The rule-based filtering approach for the manual classification of comments may not be able to accurately capture all the comments under each of the respective HBM constructs. Spelling mistakes, memes, colloquial words, and non-English comments expressing a certain health belief may not be captured.

In conclusion, this study showed that our deep learning-based text classifiers successfully yielded accurate classifications of Facebook COVID-19 comments using HBM constructs, in the context of physical distancing intervention. This further demonstrates the potential for developing deep learning prediction systems for classifying big social media data using behavioral models and frameworks. We hope that the classification model files from this study and the bulk classifier demo webpage are of practical use for public health officials and the scientific community. As a part of future work, we intend to further improve the classification models and extend our study through various approaches. First, variable length comments should be handled more efficiently. Second, we intend to experiment with a two-stage classification approach where the first stage classification is to predict whether a comment represents preventive behavior or not. The second stage classification for the filtered comments is to predict whether a comment represents any of the four HBM constructs. Third, we intend to study social media users' perceptions towards other PHA interventions such as face masks.

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Authors' Contributions

WHL conceptualized the study, interpreted the data, critically revised the manuscript for important intellectual content and provided supervision. SRA designed the study, acquired, analyzed and interpreted the data, developed the text classification model, drafted the manuscript, and critically revised the manuscript for important intellectual content. TSG annotated, analyzed and interpreted the data, and critically revised the manuscript for important intellectual content. All authors approved the final version of the manuscript.

Conflicts of Interest

None declared

Abbreviations

BA: Balanced Accuracy
CDC: Centers for Disease Control and Prevention (United States of America)
DORSCON: Disease Outbreak Response System Condition
FN: False Negatives
FP: False Positives
GRU: Gated Recurrent Unit
HBM: Health Belief Model
HDF5: Hierarchical Data Format version 5

MOH: Ministry of Healthcare (Singapore)
PHE: Public Health England
RNN: Recurrent Neural Network
SP: Specificity
SE: Sensitivity
TFJS: TensforFlow.js
TN: True Negatives
TP: True Positives
WHO: World Health Organization

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Appendix

Table A1. Sample classified comments representing perceived susceptibility

Sl. No	Facebook Comment
1	From what I see this virus is a type of pneumonia, more deadly, and contagious than that. Shouldn't the vaccine that are out there reduce the severity, or treatment be something close to it. I am at high risk of it and terrified to even go out shopping for essential things. I want a chance of surviving this.
2	Why aren't they talking about asymptomatic carriers?! It's not just people with symptoms that are spreading it and they KNOW that. ??????

3	As feedback, some parents have, by choice, have decided to take their children off school in fear of how far socially irresponsible cases have spread this. Furthermore, while we can understand why closing schools will affect working parents, there was advise for companies to try telecommuting, and working from home to control crowding and promote social distancing. Doesn't this in some way, allow a working parent the ability to be home?
4	Why are we not implementing widespread testing? Waiting for symptons to appear and for people to step forward is not enough given the increase in community spread.
5	no not a hospital, a tax office. It’s ridiculous 😣 but he has been told he’s to go. And if that site gets closed he will be moved to another. Public health is more important 😣

Table A2. Sample classified comments representing perceived severity

Sl. No	Facebook Comment
1	Now they are saying it could be 100k deaths or more! So scary!
2	I am more worried about getting the disease and dying and leaving my babies by their selves
3	Health experts have said social distancing and increased awareness resulting from the coronavirus pandemic helped end Hong Kong’s winter influenza season nine weeks earlier this time than last year, but 113 people still died of the flu. The number of deaths in the city more than halved from 356 in 2019, while intensive care unit admissions dropped from 601 to 182.
4	cnfirmed sign of community spread , school is the biggest cluster and most vulnerable one , what's the gov is waiting for before closing schools? when the case curve spikes to a certain level? pls be reminded this is life and death , not cold number or graphic . pls do not be over confident with the contact tracing method, it's proved not working any more
5	Because we are only recording cases ALREADY serious enough to be admitted to hospital, therefore more likely to die. If you don't bother testing or counting people with only mild symptoms, then of course your death rate looks worse.

Table A3. Sample classified comments representing perceived benefits

Sl. No	Facebook Comment
1	Psychologist Baruch Fischhoff, who studies decision-making, among other things, says it's fine to go outside, to go anywhere outdoors really, so long as you're committed to following the social distancing protocols as outlined by medical experts.
2	Hygiene in washing hands with soap, prevent spread wear masks to manage the prevention. Ensure the masks are N95 or 3-4 ply surgical masks. Keep a distance of 2 mtrs from people as a form of cooperation in physical distancing (social distancing).
3	“Stricter Safe Distancing “ how about the public transportation, I wondered if ours working hours can be rescheduled to 3 batches base on locations of examples 08:00-16:00 ,09:00-17:00, 10:00-18:00 and will this be help to reduce the crowd of the public transportation and the eating places
4	But meanwhile I do understand we need to keep the society running and can’t take extreme measures. Just hope that some unnecessary gatherings can be banned.
5	Stay at home to save a seniors life 👍

Table A4. Sample classified comments representing perceived barriers

Sl. No	Facebook Comment
1	If you care about your family stay home or isolate yourself in the home while you go out work. Not everyone can stay home as will starve to death and go bankrupt! This is real life....
2	Due to the situation with the coronavirus, people who are more at risk like older adult, people with allergies, diabetics, etc., should be commanded and protected by law, so they don't lose their job, to stay home until all of this pass.
3	Non of this matters if people are still able to flock to stores like home depot and lowes. There is no regulation on how many people go in the store. The parking lots are full like black friday. Someone needs to regulate these stores as they stay open for essential items.
4	1m Apart in queue is not working, at least not working at food courts, kopitiam I visited today. Even when ppl are in queue standing 1m apart on the marked floor, Sellers/Cashiers kept urging people to move forward to take their orders and payment in order to clear the queue fast. WHAT'S THE POINT THEN?
5	Stay at home ,but people who are self employed. What they can do ?

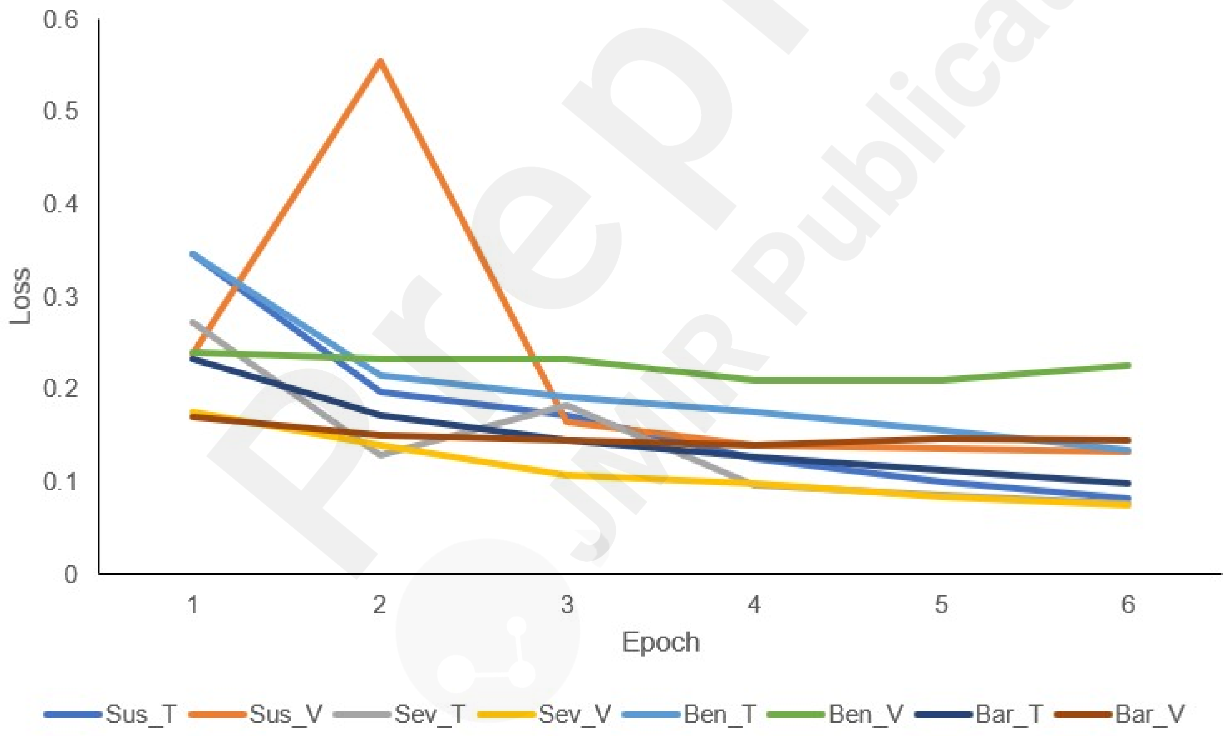
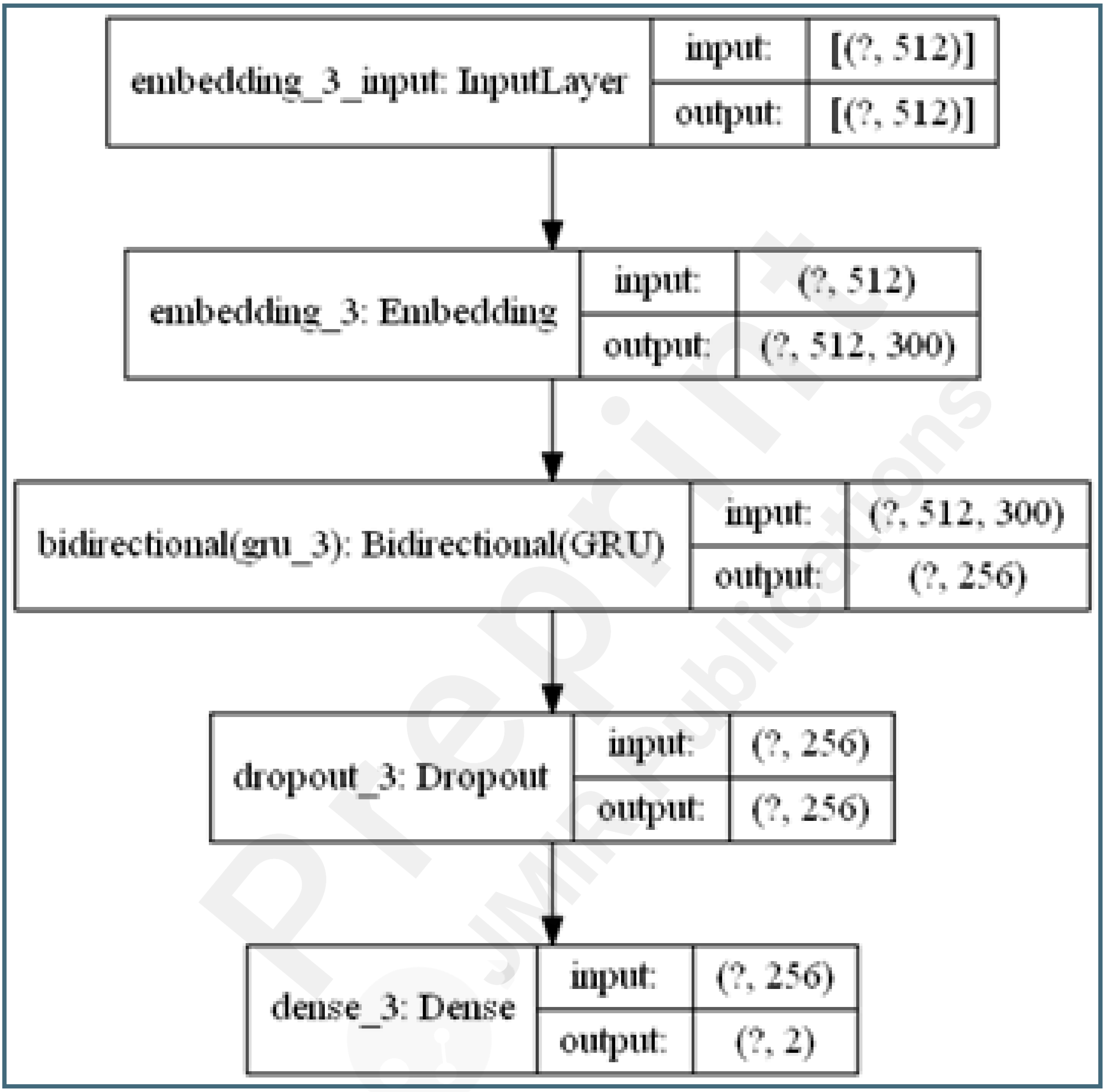


Figure A1 Loss values of the training and validation models for the four HBM constructs. *Sus* refers to perceived susceptibility, *Sev* refers to perceived severity, *Ben* refers to perceived benefit and *Bar* refers to perceived barrier. Suffixes T and V refer to training and validation sets, respectively.

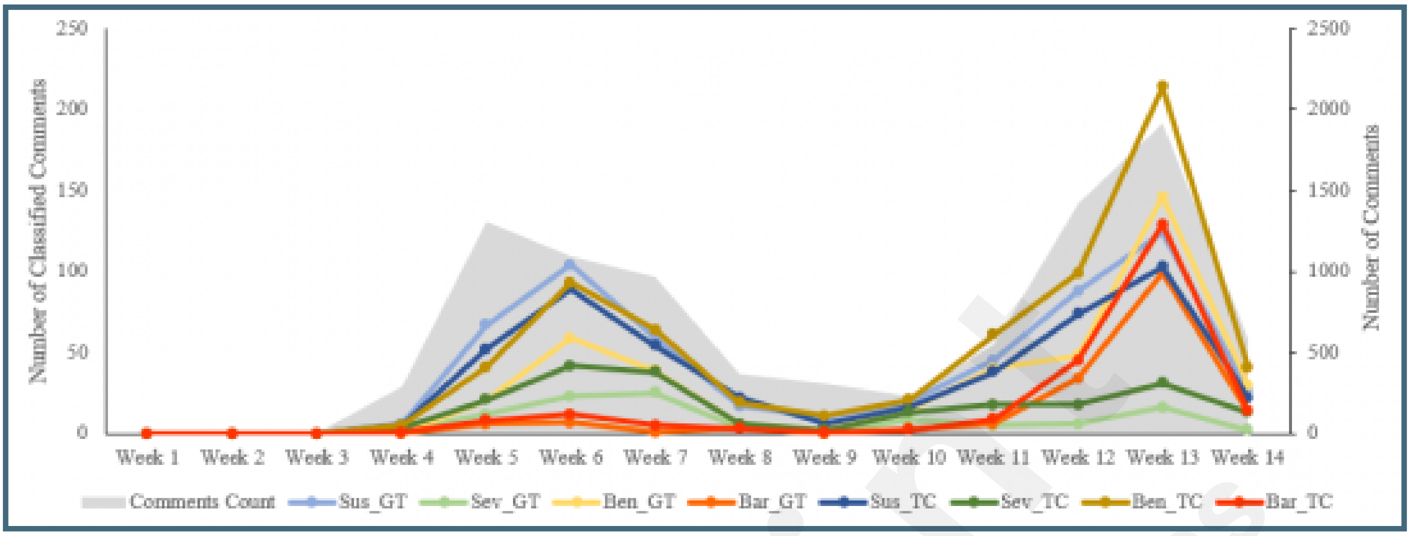
Supplementary Files

Figures

HBM Text Classifier Neural Network Architecture.



Classification of MOH Comments with HBM Constructs.



Multimedia Appendixes

Loss values of the training and validation models for the four HBM constructs. Sus refers to perceived susceptibility.
URL: https://asset.jmir.pub/assets/0abebd5b2ecb48244d4e6c240d2580e8.PNG